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Temporal Deep Learning Image Processing Model for Natural Gas Leak Detection Using OGI Camera

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Abstract

Natural gas extraction systems often encounter manufacturing defects or develop defects over time, leading to gas leaks. These leaks pose challenges, causing revenue losses and environmental pollution. Detecting gas leaks in the vast array of extraction, transfer, and storage equipment within these systems can be arduous, allowing leaks to persist unnoticed. Additionally, natural gas leaks are not visible to naked eyes, further complicating their detection.

We developed a novel deep learning image processing model that utilizes videos captured by a specialized Optical Gas Imaging (OGI) camera to detect natural gas leaks. The temporal deep learning algorithm is designed to identify patterns associated with gas leaks and improve its performance through supervised learning. Our model incorporates algorithms to detect background environments, motion, equipment, and classify gas leaks.

Our model employs leak identification algorithms to determine the presence of gas leaks. These algorithms calculate the probability of detected motion indicating a gas leak based on long-term and short-term background subtraction, detected motion, motion duration, equipment location, and telemetry data. To minimize false positives, we have developed image segmentation and object detection models to identify known objects, such as equipment, people, and cars, within the video footage. To train our model we collect more than 10,000 short videos from real fields and include simulated data with known rate controlled gas release in different situations. Data consist of wide range of weather situations including different temperature, wind speed, humidity in sunny, rainy, and snowy fields.

We validated our model by conducting experiments involving actual footage from the field. The model achieved a 98% true positive rate, and a 100% true negative rate, correctly refraining from sending an alarm for all non-releases.

Additionally, we developed a postprocessing algorithm capable of estimating the gas leak rate based on the volume of gas leaks observed in the video footage and their distance from the camera. Our experimental results demonstrate that the detected leak rates exhibit an accuracy exceeding 78%.

By employing this deep learning image processing model, natural gas extraction systems can significantly enhance their ability to detect gas leaks promptly, reducing revenue losses and mitigating environmental impact.

Introduction

The global energy landscape is defined by an intricate network of oil and gas operations that are pivotal for meeting the world's energy demands (International Energy Agency [IEA], 2020). Within this sector, managing the emissions of greenhouse gases, particularly methane from natural gas leaks, has become a focal point due to the gas's substantial impact on climate change (Intergovernmental Panel on Climate Change [IPCC], 2014). To combat this, the Oil and Gas Methane Partnership (OGMP) 2.0 framework has been introduced, setting rigorous standards for methane emission reporting and transparency (OGMP, 2020). To attain the prestigious OGMP 2.0 Gold standard, operators must validate their source/site level emissions inventory, a requirement that underscores the necessity for reliable and precise leak detection methodologies (Fox et al., 2019).

In the United States and internationally, methane emission regulations are becoming increasingly stringent. With the new EPA Subpart W, empirical source-level emissions measurement and reporting is now mandatory. Operators face hefty methane fees if their emissions exceed the baselines set in the Inflation Reduction Act. In addition, 20 countries have signed on to the Methane

Monitoring Reconciliation and Verification (MMRV) framework, which requires source-level measurement-informed inventory. Operators selling LNG to the EU, for example, will need to prove their emissions using MMRV, and face a methane fee known as the Carbon Border Adjustment Mechanism (CBAM). Other MMRV countries may adopt a CBAM.

Optical Gas Imaging (OGI) technology has become an essential tool for operators to observe and quantify emissions, enabling them to address compliance and exceed the expectations of voluntary initiatives like OGMP (Wang, 2022) enabling operators to visualize emissions that are otherwise invisible to the naked eye (IPCC, 2014). However, traditional methods for processing OGI data rely heavily on manual interpretation, demanding significant operator expertise and time. This has led to a significant interest in automated systems that enhance the efficacy and accuracy of the leak detection process (Kemp et al., 2016). Deep learning, a subset of machine learning that utilizes neural networks with multiple layers, has shown promise in complex image recognition tasks and is being increasingly applied for environmental monitoring applications (Cusworth et al., 2021).

While static image analysis for leak detection has seen considerable development, temporal deep learning models that leverage the dynamic nature of video data remain less explored. The transient and variable visual patterns of gas leaks present unique challenges that static models may fail to address effectively (Cusworth et al., 2021). Capturing temporal correlations within video frames can provide a more robust detection mechanism sensitive to the movement and evolution of gas emissions over time (Lee et al., 2019, Wang et al., 2020).

This paper introduces a novel Temporal Deep Learning Image Processing Model (TDLP-NG) designed to enhance natural gas leak detection using OGI cameras. Our model incorporates convolutional neural networks (CNNs) for spatial feature extraction, and recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) units to capture temporal dependencies. The architecture of TDLP-NG allows it to learn from both the spatial context within individual frames and the temporal progression across frames, enabling it to distinguish between gas leaks and visually similar but irrelevant phenomena such as steam or dust.

In summary, TDLP-NG offers a state-of-the-art approach for automated gas leak detection, addressing the limitations of existing methods and setting a new benchmark for accuracy and reliability in environmental monitoring. The remainder of this paper is organized as follows: the next section provides related work; then we provide the modeling and data processing and explain the results part; in the last section we discuss conclusion and future works. By integrating deep learning with OGI technology, TDLP-NG represents a significant advancement in the pursuit of safer and more environmentally sustainable natural gas operations (IEA, 2020; OGMP, 2020; Fox et al., 2019).

Literature Review

Methane emissions from the oil and gas industry represent a significant contribution to global greenhouse gas levels, with methane being over 25 times more potent in terms of global warming potential than carbon dioxide over a 100-year period (IPCC, 2014). Effective detection and management of these emissions are critical for environmental sustainability and regulatory compliance (Fox et al., 2019).

Recent years have witnessed advancements in methane detection technology, with Optical Gas Imaging (OGI) proving particularly useful for its ability to visualize gas leaks that are invisible to the naked eye (Jackson et al., 2020, Ravikumar et al., 2018). OGI cameras, operating within specific infrared wavelengths that methane and other hydrocarbons absorb, have been transformative, enabling quicker identification of leaks across extensive infrastructure (Fox et al., 2019).

Despite their advantages, manual analysis of OGI video data is notably subjective and labor-intensive, presenting challenges in scaling up for comprehensive monitoring (Lee et al., 2019). As a result, there has been a marked shift towards the development of automated deep-learning-based approaches capable of effectively processing the imaging data produced by these cameras (Cusworth et al., 2021).

In the search for automated solutions, several studies have emerged. Cusworth et al. (2021) explored convolutional neural networks (CNNs) for spatial feature detection in static OGI images. While their model demonstrated improved detection rates, it did not fully leverage the temporal dynamics present in video data, which are crucial for identifying and distinguishing between different types of gas patterns and other visual artifacts like steam or dust (Cusworth et al., 2021).

The recognition that methane patterns display distinct temporal behaviors led researchers such as Wang (2022) to investigate recurrent neural network (RNN) architectures, including Long Short-Term Memory (LSTM) models, capable of capturing time-series data within video sequences (Wang, 2022). Their work laid the groundwork for temporal analysis in OGI data processing, but it did not completely integrate the spatial-temporal analysis necessary for comprehensive detection.

Our TDLP-NG model is designed to address these gaps. By utilizing a hybrid neural network architecture that combines CNNs for spatial feature extraction with LSTMs for capturing time-dependent data, our model provides a novel approach that is finely tuned to the specific challenges associated with OGI-based methane leak detection. The model was developed with the complexity of the optical patterns produced by methane emissions in mind, ensuring robustness against false positives and improved accuracy in leak identification. We also develop rate estimation model on top of the gas leak detection to future enhance the capability of the model for detection and provide more knowledge to the field engineer about the size of the leak.

The relevance of this work is further underscored by industry shifts towards voluntary reporting standards such as the Oil & Gas Methane Partnership (OGMP) 2.0 framework. As operators aim to achieve the Gold Standard under OGMP 2.0, there is a pressing need for precise and scalable leak detection and quantification methods, necessitating technological solutions like TDLP-NG that can reliably capture emissions at the required granularity (OGMP, 2020).

Moreover, adherence to the OGMP 2.0 framework can also facilitate compliance with regulatory requirements, while demonstrating a commitment to best practices with respect to methane emissions monitoring. It reflects the industry's increasing recognition of the importance of accurate emissions inventory and the role of advanced technologies in achieving these objectives [IEA, 2020].

In addition to OGI , Laser heterodyne radiometry (LHR) stands as a notable technique with a history of use since the 1970s for the measurement of atmospheric trace gases (Deming et al., 1973; Sonnabend, 2002; Menzies & Shumate, 1974; Melroy 2015). LHR operates on a principle analogous to that of a radio receiver, transforming light signals into detectable electrical frequencies that can be used to analyze gas concentrations against known absorption spectra (Deming et al., 1973; Sonnabend, 2002; Menzies & Shumate, 1974; Melroy, 2015). Recent innovations have revolutionized this technique, giving rise to a miniaturized and passive form that utilizes low-cost distributive feedback (DFB) lasers. This modern iteration of LHR, the mini-LHR, has been specifically crafted to quantify the concentrations of pivotal greenhouse gases such as CO2 and CH4 by gauging their absorption of sunlight within the infrared spectrum (Faist et al., 1994; Silver et al., 2000; Wysocki et al., 2008). Unlike its traditional counterparts that require large and complex setups, the mini-LHR employs a sun tracker-connected collimator to capture sunlight, akin to an antenna receiving radio signals. This advancement in LHR technology represents a significant stride in passive atmospheric gas sensing, promoting both portability and cost-effectiveness (Faist et al., 1994; Silver et al., 2000; Wysocki et al., 2008).

While LHR offers substantial benefits for atmospheric monitoring, its application to industrial leak detection, particularly in oil and gas operations, presents limitations. The need for direct sunlight and the complexity of correlating diffuse sunlight with specific leak sources render LHR less practical for localized, actionable leak identification within the intricate infrastructure of these industries.

Therefore, the TDLP-NG model embodies the intersection of industry need and academic innovation, providing a solution that aligns with both current and emerging frameworks for methane emissions monitoring. This seamless integration of spatial-temporal analysis into OGI data interpretation represents a significant leap forward in the quest to mitigate the environmental impacts of hydrocarbon extraction and processing.

Modeling

As the preliminary step in addressing the challenge of methane leak detection, our study was purposefully designed to exploit the technical strengths of Optical Gas Imaging (OGI) technology in tandem with temporal deep learning techniques. The central objective of the study was to engineer a robust model capable of accurate and efficient detection and quantification of methane leaks from video data. This aspiration required not only a meticulously curated dataset but also the development of a sophisticated model architecture—capacity both to pinpoint spatial characteristics and to track temporal patterns of methane emissions—hence, the inception of the Temporal Deep Learning Image Processing Model (TDLP-NG).

The operational phase commenced with the strategic deployment of OGI cameras at select locations throughout natural gas facilities. Equipped with specialized infrared sensors sensitive to the spectral signature of methane gas, these cameras served as the eyes of our study, capturing real-time footage of the operational landscape. The meticulous arrangement considered a multitude of variables—distance, angle, and environmental factors—to calibrate the instrumentation for optimal gas leak visualization. Satisfactory deployment yielded a treasure trove of video sequences that constituted the raw material for the subsequent data processing pipeline.

Data Collection

The initial phase of our study involved a comprehensive data collection process using Optical Gas Imaging (OGI) cameras specifically designed to detect methane emissions. The cameras were positioned at various sites known for natural gas extraction and processing to capture a diverse range of leak scenarios. The acquired video footage provided a rich data set, including instances with varying gas plume densities, environmental conditions, and background scenery.

Collected video data were subjected to rigorous labeling protocols. Emission events within the footage were annotated by trained professionals, highlighting regions containing methane plumes. Each labeled instance was timestamped to ensure temporal accuracy, a critical aspect for subsequent processing by the Temporal Deep Learning Image Processing Model (TDLP-NG).

Data Preprocessing

Prior to being introduced into the deep learning model, the video frames underwent a thorough preprocessing routine. This involved frame extraction at a rate conducive to capturing the dynamic behavior of gas plumes while remaining computationally manageable. Each frame was standardized in size and resolution, and a normalization process was applied to ensure consistency in pixel distribution and intensity.

Noise reduction techniques were employed to enhance the visibility of the methane emissions within the frames. Considering the inherent complexity of backgrounds in industrial settings, a bespoke filtering algorithm was developed to improve signal-to-noise ratios, thus emphasizing the spectral patterns unique to methane.

Temporal Deep Learning Image Processing Model (TDLP-NG)

The cornerstone of our methodology was the development of TDLP-NG, an innovative deep learning architecture crafted to detect and analyze methane emissions within OGI video data. By harnessing the combined power of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) units, the model delivers unprecedented spatial-temporal analysis capabilities.

CNN Architecture: Our model's CNN component was designed to extract high-level feature representations from individual frames. A sequence of convolutional and pooling layers systematically distilled the raw pixel data into an abstracted form, better suited to classification and localization tasks associated with gas leak detection.

LSTM Integration: The temporal aspect was addressed by integrating LSTM units following the CNN feature extraction. LSTMs are adept at recognizing patterns across sequences, making them an ideal choice for capturing the dynamic evolution of methane patterns over time. The LSTM layers analyzed the sequence of CNN-derived features to predict the presence and characteristics of emissions.

Loss Function and Training: A custom loss function was designed to simultaneously optimize the spatial precision of detected plumes and the temporal correlation across frames. The model was trained on a curated dataset using backpropagation through time, a suitable optimization algorithm for temporal data. Several epochs with varying hyperparameters were executed to refine model accuracy.

Data Augmentation: To enhance the model's robustness, data augmentation techniques were applied. This included transformations such as rotations, translations, and scaling, which allowed the model to become invariant to certain variabilities in the data that do not alter the presence of methane emissions.

Auxiliary Models

We have developed different models to help to improve the accuracy of the actual gas leak detection model including background subtraction, equipment and object detection models; motion detection and leak identification algorithms, i.e.,

1. **Background Detection Algorithms**: These algorithms discriminate the background environment from the areas of interest in the video footage. They perform long-term and short-term analysis by comparing pixel values across multiple frames to identify static elements of the scene and subtract them out, focusing on regions where changes may indicate potential leaks (Sullivan 1994).

2. **Motion Detection Algorithms**: These algorithms detect movement by comparing pixel values across consecutive frames. Any discrepancy points to motion, which may be from a gas leak or another source. By identifying areas of motion in the video, the system can focus on analyzing these regions for leak characteristics (Haritaoglu et al., 2000).

3. **Equipment Detection Algorithms**: The goal of these algorithms is to locate and identify the tanks and other equipment in the video footage. By recognizing equipment, the system can determine potential origins of leaks and correlate detected movements with specific pieces of equipment (Mirzaei, 2016).

4. **Leak Identification Algorithms**: These algorithms work to assess the likelihood that the motion detected is, in fact, a leak. It combines data from the previous steps with telemetry data (e.g., pressure, temperature) to ascertain whether an observed movement corresponds to a gas leak. Factors like motion duration, location relative to equipment, and telemetry data form the basis of calculating gas leak probability (Kwaśny, 2023).

5. **Object Detection Models:** These models are crucial for reducing false positives. They segment frames to correlate movement with known objects or segments, identifying regions as equipment, vehicles, or personnel, and helping to relate each leak with probability to an actual device in the field (Redmon and Farhadi, 2018).

6. **Non-linear Function Model:** The system employs a non-linear function model that aggregates outputs from the other models. It processes these outputs to confirm or reject the detection of a gas leak. This function performs a series of subtractions that take away parts of the image data identified as background or equipment, focusing on motion that does not belong to either of these categories. When overlaps occur between the substructions and regions identified by the gas leak detection model as potential leaks, the non-linear function confirms the presence of a gas leak. The function outputs a probability/confidence metric on the existence of the gas leak and may also provide a gas flow rate estimate (Baroudi, 2019).

Validation and Testing

The validity of TDLP-NG's detection was comprehensively assessed through a validation phase, involving a set of reserved video data. A comparison between model predictions and expert annotations served to fine-tune the model parameters and solidify its detection efficacy.

A battery of tests was also conducted on entirely unseen data to challenge TDLP-NG's generalization capabilities. The results were quantitatively evaluated using metrics such as precision, recall, and the F1 score, ensuring that the model performed at a high standard when faced with new, unlearned scenarios.

All testing results were independently reviewed by the Colorado Department of Health & Environment (CDPHE) as part of it's Alt-AIMM (alternative approved instrument monitoring method) process. Results were also reviewed by EPA Region 8.

Rate Estimation

Gas leak rate estimation models based on optical flow leverage the apparent motion of gas leak patterns in video sequences to infer leak rates (Qiao, 2017). Optical flow algorithms analyze the movement of gas pixels between consecutive frames, enabling the estimation of the velocity and direction of the moving gas patterns. These flow fields can then be converted into leak rate estimates through a variety of approaches.

To estimate the rate of a gas leak using an optical flow-based model, various factors are taken into account, including the properties of the plume captured by OGI cameras, the distance of the camera from the leak, and the camera's lens angle. Each pixel of image represent larger areas for further leaks vs close ones, which contribute into the rate estimation model.

The workflow for estimating gas leak rates with an optical flow-based model is as follows:

1. **Plume Detection**: The optical flow algorithm is applied to consecutive frames of a video to detect the gas patterns and compute the per-pixel movement within the plume region. This flow field represents the movement of the gas over time.

2. **Flow Field Analysis**: By analyzing the flow field, the model can interpret the speed and direction of the gas plume. This speed can be correlated to the leak rate, but without additional information, it only provides a relative measure of the flow rate. This actually represent the pixel movement speed and direction. We used machine learning model to translate the pixel movement into the gas rate by including other information like weather, distance of camera to the leak and angel of the camera lens.

3. **Machine Learning Model Integration**: For the machine learning model, we create a training datasets where actual leak rates are known, is used to correlate characteristics of the flow field with leak rates. The model incorporate features extracted from the flow field and other environmental factors to estimate the actual leak rate. In Fig 1 we presented the accuracy of our model based on a golden dataset.

4. **Distance and Angle Calibration**: The distance between the camera and the leak impacts the scale of the observed plume on the camera's sensor. Similarly, the angle of the camera's lens can distort the plume shape. The model needs to be calibrated to account for these factors. This can be done by knowing the camera specifications (focal length, sensor size) and using trigonometry to adjust the perceived plume dimensions to real-world measurements.

5. **Estimate Leak Rates**: With the flow field analyzed, and accounting for camera distance and angle, the machine learning model can estimate the actual leak rate. The model has been adequately trained on a wide variety of leak circumstances, including various distances and angles to make it generalize well to new data.

6. **Model Refinement**: As the model is deployed, it can continually be refined and updated with new data. This iterative process is crucial in environments where plume characteristics can change due to factors such as wind velocity, background, temperature, and equipment variations.

By integrating optical flow with machine learning and accounting for camera specifications, our model provide accurate and robust leak rate estimations. We also integrate gas properties such as temperature, pressure, and methane composition to further refining the estimation of the leak rate. As a point of calibration, actual measured leak rates may be used to validate and adjust the model to ensure accuracy and reliability.

Results

The results of the paper centered around the TDLP-NG detection, which demonstrated effectiveness in detecting natural gas leak emissions, localizing their sources, and enabling operators to promptly respond and rectify the causes of these emissions. Two case studies in the paper illustrated this point:

- In the first case study, TDLP-NG detected an emission event. The system not only promptly spotted the leak but also identified its exact source of detection. The source, an incomplete combustion event from a fire tube stack, was confirmed using the system's OGI video.
- The second case study detailed a continuous emission that was tracked over three days, showcasing the resilience of the system to changing environmental conditions. The TDLP-NG system detected the event and identified an unlit fire tube as the source of emission

In addition to presenting field deployment case studies, we provide a controlled release testing technique using archival OGI video footage as a stopgap measure before conducting blind controlled release field testing. The use of archival OGI video allowed for preliminary performance metric data collection to inform simulation modeling.

- In the first study, of the 92 video footage, 82 (approximately 89%) were correctly classified by the TDLP-NG detection algorithm. Correct classification meant that videos with emissions were identified as such, and videos with no emissions (during non-release periods) were accurately marked as not containing emissions.
- In the second testing a total of 63 releases and 63 non-releases were tested. The TDLP-NG System identified 62/63 releases (98% true positive rate) and correctly ignored 63/63 non-releases (100% true negative rate).

In another experiment, we tested the accuracy of the model for different distances, and also estimate the rate of the leak. Fig. 1-4 show the actual detection and bounding box around movement for couple of samples. For each figure, we also stated the rate of the detection. Table 1 illustate the dectection accuracy (true possitive and true negative) for different distances.

We also estimate the detection rate using optical flow. Fig. 5 shows Rate estimation of actual events using distance of the camera to the event, camera angel, weather information and optical flow of the video footage.

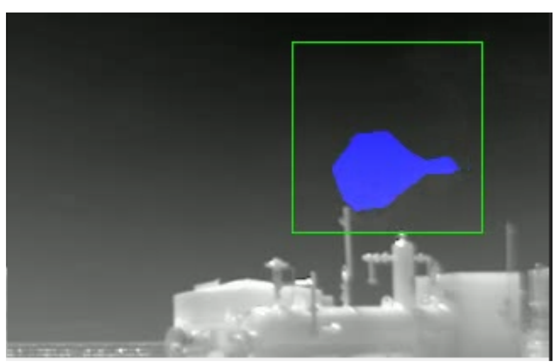


Fig. 1: Processed footage of a correct detect.
Distance: 18.6m, emission rate: 124.3 ± 2.9 scf/hr (2051.6 ± 48 kg/hr)

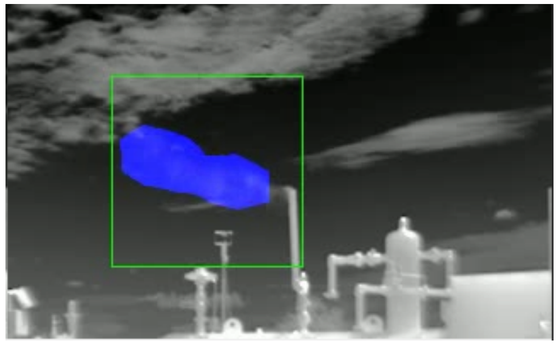


Fig. 2: Processed footage of a correct detect.
Distance: 15.6m, emission rate: 124.3 ± 2.9 scf/hr (2051.6 ± 48 kg/hr)

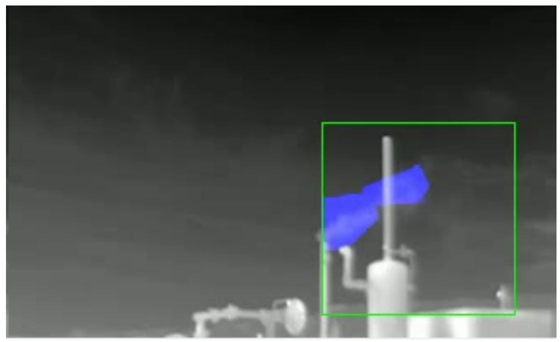


Fig. 3: Processed footage of a correct detect.
Distance: 15.6m, emission rate: 109.5 ± 2.5 scf/hr (1806.1 ± 41.4 g/hr)

Fig. 4: Processed footage of a correct detect.
Distance: 18.6m, emission rate: 109.5 ± 2.5 scf/hr (1806.1 ± 41.4 g/hr)

Table1 — Results of blind controlled release testing at a based well production facility

Testing Distance (meters)	True Positive Ratio	True Negative Ratio
40	14/15	15/15
60	15/15	15/15
80	15/15	15/15
100	10/10	10/10
120	8/8	8/8

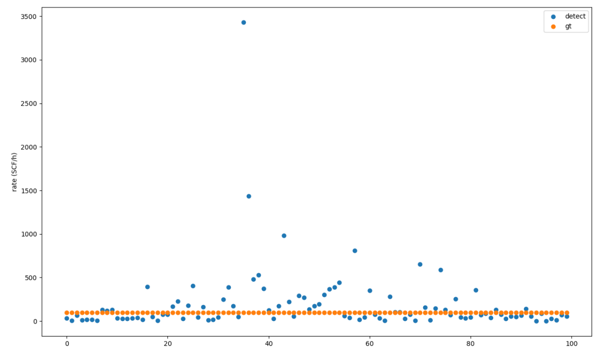


Fig. 5 : Rate estimation of actual events using distance of the camera to the event, camera angel, weather information and optical flow of the video footage

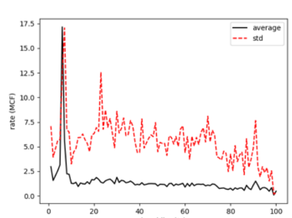
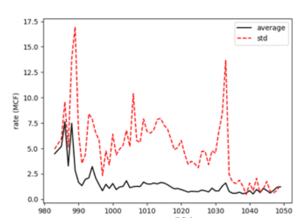
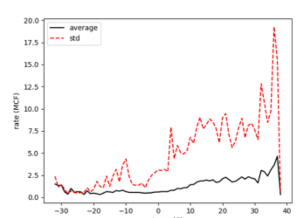
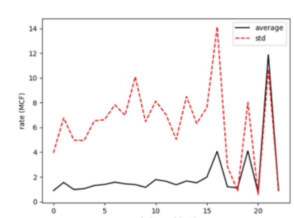
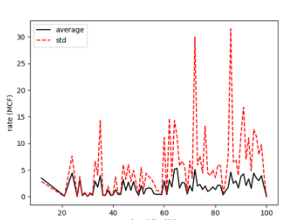
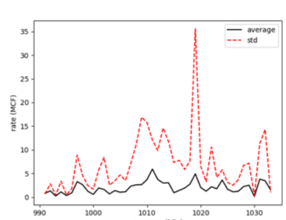
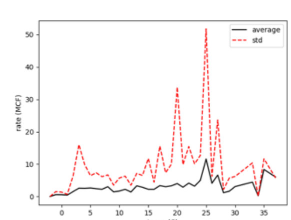
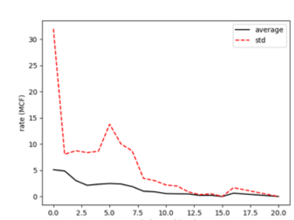
The system's high accuracy in detection under various conditions and its ability to function with archival OGI footage demonstrate its robustness, making it a promising tool for the industry to swiftly identify and mitigate natural gas leaks.

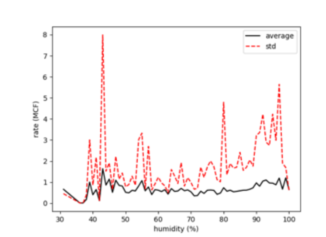
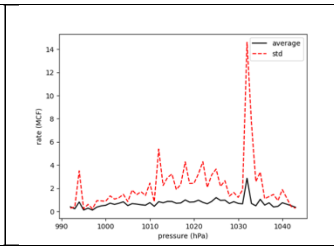
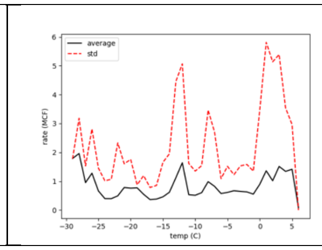
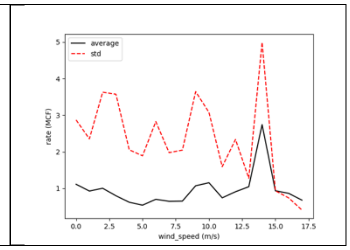
Weather Effects

Weather conditions unquestionably play a critical role in the detection of gas leaks and the estimation of their rates. We analyzed three weather conditions (Clear, Rain and Snow) under different humidity, pressure, temperature and wind conditions. While motion analysis of gas plumes may be hindered under certain conditions, particularly with high wind speeds which can disperse gas plumes rapidly, making detection and accurate rate estimation challenging, Table 2. Also high temperatures may cause thermal interferences with detection technology during the summer, and it has negative effect even on the camera and node performance.

Our approach to considering different weather condition is to utilize statistical models that incorporate atmospheric data to normalize the impact of weather conditions. We trained a machine learning models on top of the leak detection to estimate leak rates under various weather conditions, allowing the model to learn the patterns that correspond to leaks irrespective of the prevailing weather. Our model takes into account sensor data and compensate for the reduced visibility in adverse conditions such as rain or snow by relying more on other indicators of leaks that are less sensitive to weather, like the chemical signature captured by advanced sensors.

Table 2 - Effect of weather (clear, rain, snow) on rate estimation under different humidity, pressure, temperature and wind
Higher wind has very negative effect on rate. Also high summer temperature may distort rate estimation and detection. Pressure or humidity may not play big role compare to wind and temperature in clear weather. Obviously, detection in rain and snow may not be as good as clear environment.

Weather	Humidity	Pressure	Temperature	Wind
Clear				
Rain				

Snow				

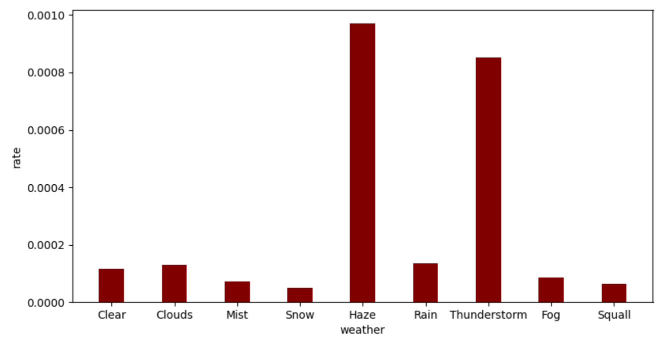


Fig. 6: Rate estimation in different weather conditions, haze weather and thunder storm has negative effects on the rate estimation

Inference

In the realm of natural gas leak detection, the deployment of computational models for processing and analyzing video feeds from optical gas imaging (OGI) cameras constitutes a significant challenge, particularly given the remote and oftentimes isolated nature of many gas facilities. These sites typically lack a stable and high-bandwidth internet connection, which precludes the continuous streaming of high-volume video data to cloud-based computing platforms for analysis. Consequently, this necessitates a paradigm shift in data processing methodologies, moving away from centralized cloud computing towards a more distributed edge computing framework.

Edge computing refers to the processing of data at or near the data source, which in this case would be the OGI cameras mounted at the gas facilities. By deploying deep learning models on edge nodes positioned in close proximity to the cameras, real-time analysis of video feeds can be conducted without the need for constant data transmission to a remote cloud server. This on-site analysis enables the rapid detection of gas leaks, thereby enhancing response times and mitigating potential hazards more effectively.

However, the deployment of sophisticated deep learning models on edge nodes is constrained by the limited computational resources available at these fringe computing environments. Edge nodes are typically less powerful than centralized cloud servers and are equipped with lower computational capacity, memory, and storage. As a result, we are faced with the pivotal task of optimizing our temporal deep learning image processing models to operate efficiently within these constraints.

Optimization may encompass various strategies, such as refining the architecture of the neural network to decrease its computational complexity, leveraging model compression techniques to reduce the size of the model without significantly impacting its performance, or employing specialized hardware accelerators that are tailored for edge computing scenarios. By engaging in these optimization practices, it becomes feasible to maintain the fidelity and accuracy of the gas leak detection models while adhering to the resource limitations inherent to edge nodes.

In the context of optimizing deep learning models for deployment on resource-constrained edge nodes, a key technique is pruning—the systematic removal of non-essential components from a neural network. The overarching goals of pruning are multifaceted: it serves to lessen the model's memory demands, bolster its robustness against novel inputs by enhancing generalization, expedite inference operation, and permit model training with a reduced dataset.

Pruning is divided into distinct methods, each with its benefits and limitations, notably structured versus unstructured pruning, as well as local versus global approaches. Structured pruning targets entire groups of parameters, such as neurons, layers, or channels for convolutional neural networks. This method diminishes matrix multiplications and might yield a faster inference time due to the simplified architecture. However, structured pruning comes with the caution that overly aggressive reductions might degrade model performance significantly, as entire critical structures could be eliminated.

Conversely, unstructured pruning zeroes in on individual weights throughout the network. The selective nature of this pruning allows for a high degree of parameter reduction while preserving model integrity. The main drawback is that such granular pruning might not lead to actual computational gains on specific hardware, as the resulting sparsity does not inherently speed up operations on systems optimized for dense matrices.

The choice between local and global pruning further complicates the optimization process. Local pruning uniformly trims parameters from each layer, maintaining network stability but potentially missing opportunities for more substantial overall sparsity. Global pruning, which prunes across the entire network, can more adeptly shrink the model by focusing on the least crucial parameters. The risk here is causing disproportionate parameter loss in vital layers, which could undercut the model's learning capacity.

The intricacies of pruning underscore the need for a deep understanding of model architecture and the constraints of the edge computing environment. It is essential to finely tune the extent of pruning in sync with the deep learning model's performance demands, such as those required for the precise detection of natural gas leaks using OGI cameras. Achieving the delicate equilibrium between model size, speed, and accuracy is an iterative process, demanding repeated experimentation with various pruning ratios and techniques to determine the most appropriate method for a given application. Table 3 shows the comparison of the different model optimization techniques.

Table 3 - shows comparison of different pruning methods applied on the gas leak model on Nvidia AGX Orin edge node. We used 170 videos with 2 min lengths to compare the speed of the inference time.

Pruning # of parameters = 10M	Pruning Ratio	Accuracy	Run Time Minute	Inference Time
Original Model	-	127/159	1:16	0.0420
Global Unstructured Pruning (Magnitude, L1 norm)	0.15	123/159	1:16	0.0418
Local Unstructured Pruning (Magnitude, L1 norm)	0.15	122/159	1:15	0.0411
Local Unstructured Pruning (Random)	0.15	38/159	0:57	0.041
Local Structured Pruning (Magnitude, L1 Norm)	0.15	77/159	1:07	0.0416
Local Structured Pruning (Magnitude, L2 Norm)	0.15	65/159	1:06	0.0413

Based on the Table 3, local structured pruning method is the best one that does not affect the accuracy a lot. In Table 4 we compare different ratio of local structured pruning method. Fig. 7 shows the accuracy of the local structure pruning method based on different ratios.

Table 4 - Performance of the model on the AGX node using different ratios of local structured pruning method

Method	Ratio	Video Run Time second	Accuracy (out of 170)
Original Model	0.0000	42	157
Local Structured (Magnitude, L2 Norm)	0.025	38.89	146
Local Structured (Magnitude, L2 Norm)	0.02	39.89	137
Local Structured (Magnitude, L2 Norm)	0.03	38.58	141
Local Structured (Magnitude, L2 Norm)	0.045	38.17	137
Local Structured (Magnitude, L2 Norm)	0.055	37.17	127
Local Structured (Magnitude, L2 Norm)	0.07	38.54	130
Local Structured (Magnitude, L2 Norm)	0.08	38.26	126
Local Structured (Magnitude, L2 Norm)	0.0825	37.13	118
Local Structured (Magnitude, L2 Norm)	0.09	36.663	111

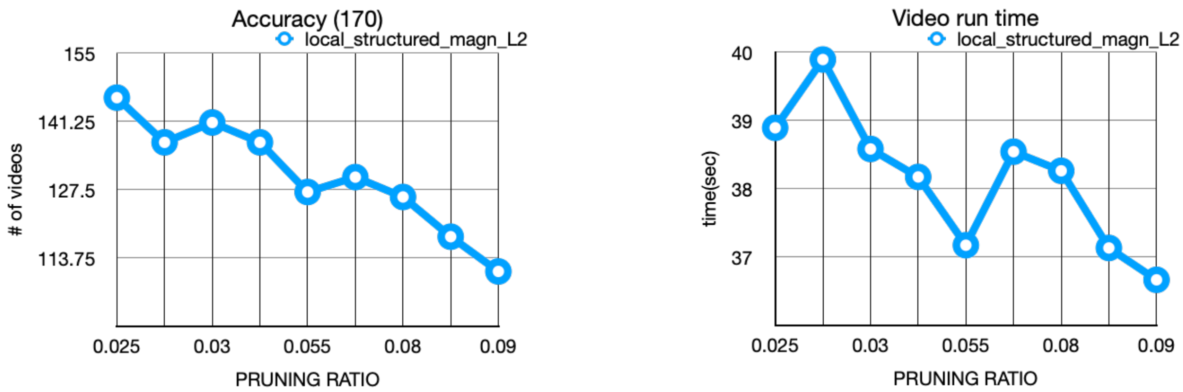


Fig 7. accuracy of local structure pruning method on the gas leak model for 170 videos

Deployment

When implementing our model on an edge node and interfacing it with an Optical Gas Imaging (OGI) camera in the field, several challenges arise. Many of these challenges stem from difficulties related to the camera itself, such as malfunctions due to overheating and core damage. Moreover, the stability of the camera's mounting is crucial for acquiring steady images free from disturbances. Camera shake can be a substantial issue, especially when wind and storms create significant vibrations, complicating the leak detection process.

Additionally, the camera may inadvertently capture movements in the environment that mimic the appearance of gas leaks, such as swaying grass or trees. These false indicators are typically filtered out in post-processing through object detection and equipment recognition models.

Another complication involves misinterpretation caused by shadows and reflections; we have mitigated this through extensive training with a more diverse set of samples. Similarly, phenomena like exhaust emissions, the glow of a lit flare, or heat from a firetube can generate patterns resembling gas leaks. Enhancements to our model's recognition abilities targeted these particular scenarios, refining its discernment capability. Table 5 presents a breakdown of the false positive rates within our system's output, along with their attributing causes, further elucidating the sophistication of our detection process.

Table 5 – False positive reason in the production environment

False positive Reason	Camera Shake	Exhaust Heat	Lit Flare Firetube	No Image	No Visible Detection	Object Movement	Shadow Reflections	Other
FP error percentage	3.42%	11.44%	27.30%	0.87%	33.73%	5.74%	17.25%	0.22%

Summary

The paper introduces a Temporal Deep Learning Image Processing Model (TDLP-NG) for detecting natural gas leaks using Optical Gas Imaging (OGI) cameras. This novel deep learning model aims to identify patterns associated with gas leaks and improves its performance through supervised learning. The TDLP-NG is designed to work with videos and employs leak identification algorithms to calculate the probability of a detected motion being a gas leak, using background subtraction, motion duration, equipment location, and telemetry data. The TDLP-NG leverages convolutional neural networks (CNNs) for spatial feature extraction and recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) units to capture temporal dependencies. The model's design facilitates distinguishing between gas leaks and other phenomena such as steam or dust, by evaluating both the spatial context within individual frames and the temporal progression across frames.

To reduce false positives, the model incorporates image segmentation and object detection algorithms to identify known objects in the footage. The training dataset consists of over 10,000 short videos from real fields, as well as simulated data with known controlled gas release rates under various weather conditions. Empirical validation demonstrated a 98% true positive rate and a 100% true negative rate, and a postprocessing algorithm for estimating leak rates showed an accuracy exceeding 78% which represents a state-of-the-art approach for automated gas leak rate detection and signifies an important advancement in promoting safer and more sustainable natural gas operations.

The paper also discussed optimizing deep learning models for deployment in remote gas facilities with limited computational resources. Due to the remote locations of gas facilities which often lack stable and high-bandwidth internet connections, there is a need to move from centralized cloud computing towards an edge computing framework. The paper discussed optimization strategies using different pruning techniques to trade-offs between decreasing model size and preserving performance.

In the future work, the extension of the model will enhance the postprocessing algorithm used for estimating leak rates to improve the accuracy of leak quantification, by integrating 3D modeling, weather data like wind speed. We also want to explore the deployment of the TDLP-NG model on unmanned aerial vehicles (UAVs) for automated monitoring of extensive gas infrastructure networks. To Deploy the model on UAVs we need to stabilize the video stream from the UAVs to have more stable input to the model. In addition hardware optimization play a big role on UAVs to ensure that the OGI cameras and processing units can handle the computational load of the deep learning algorithms to make the solution more practical with limited energy resources. For more practical solutions for widespread deployment we can also combine the deep learning model with data from additional sensors, like laser, to improve the accuracy of leak detection and localization.

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